A Predictive Approach for Efficient e-Health Monitoring

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***Abstract*—In this work, we propose an efficient health-care monitoring system for the daily home activity of persons. We intend to combine a good optimization of the resources (e.g. network and energy) and an automatic evaluation of the person's dependency while ensuring a high accuracy for detecting unusual behaviors. The proposed system considers the person's context and predicts the health condition based on the usual behavior and energy consumption for each daily activity. The proposed system requires a minimum set of sensed data with short training periods for predicting the person's behavior changes.**

I. Introduction

The number of elderly persons around the world has recently increased. Health care quality of service and social cost are negatively affected by this aging population and the progressive decline of their physical and cognitive skills, which prevents them to independently perform daily activities. Traditional health monitoring systems predominantly tend to sense all of the available data in a continuous way and with an unconditional processing. Several problems rise with such approach such as collapse of the network, data transmission failure, ineffective energy consumption, important computational cost and loss of priorities in processing, high complexity and failure in understanding the person's behavior and to make quick relevant decisions.

Context-aware e-health systems should have a clear visibility of the person's context. This visibility includes a good understanding of the person's lifestyle (the usual person's behavior) to perform daily activities and the ability to perceive and extract any change of person's behavior. In our previous investigation [1], we provided a better understanding about the context of monitored persons, which is the set of activities of daily living that should be monitored in e-health monitoring systems. In this paper, we propose a predictive and optimal approach for e-health monitoring in smart environments. The objective of the proposed approach is to ensure efficient sensing frequencies and combine a good optimization of the resources with a good credibility in evaluating the dependency of monitored persons. The optimization of resources concern many dimensions like computing, network traffic and energy consumption. Moreover, our goal is to provide a high accuracy for detecting the abnormal and unusual situations for all the levels of the person's dependency. Our system targets gaining the ability to extract and predict the health condition of persons. Our approach is based on a good knowledge of the person's behavior and the usual energy consumption for each activity with only short training periods and minimum amount of sensed data.

II. Related Work

The general structure of health-care monitoring systems (HMS) includes sensor devices, communication technology and processing systems. The smart processing is the heart and most complex part [2] of a HMS, as it is the component which is responsible for main controlling operations like: setting the sensors, communication and data analysis, recommendation services, etc. HMS for elderly people are aimed at monitoring and evaluating functional abilities in order to achieve daily activities correctly [3]. The success of an intelligent HMS is measured by its ability to understand the normal behavior of elderly people and to predict and detect abnormal behaviors [4]. There are several studies and methods which have been designed to optimize the behavior prediction system. Probabilistic concepts to predict actions by using Hidden Markov Models (HMM) are used in [5]. Neural networks and machine learning techniques are used in [6] to define patterns of daily activities to be used for predictive models. Naive bayesian network approachs are proposed in [7], and decision trees in [8]. Support Vector Machines (SVMs) were used in [9]. Clustering approaches and fuzzy membership functions are used to define fuzzy rules of data collected for activity prediction [10]. A data driven system was presented in [4] by using temporal and spatial contextual activity data. Case-based reasoning rules were proposed in [11].

Most of the existing studies share the same challenges and main difficulties like: identifying an optimal prediction method, the need of long training period, the analysis of a huge amount of data and the need to perform a continuous monitoring all the time whatever the person's context. Therefore there is an urgent need for designing an efficient system combining an optimal monitoring cost with an accurate prediction of the person's behavior. We propose a predictive and context-aware monitoring system able to collect relevant and contextual data, detect abnormal behaviors and evaluate the person's dependency while remaining cost-efficient.

III. Methodology

Health monitoring systems should take into consideration several factors for an efficient monitoring and evaluation of persons. Mainly, factors are related to the person's health condition including: the person's level of dependency, regular

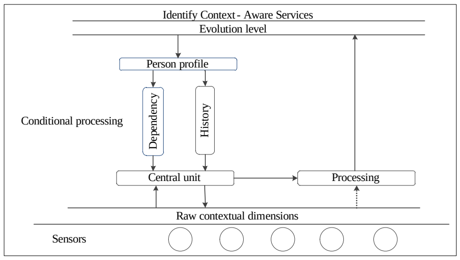

Fig. 1. Request-driven monitoring scheme

and periodic human behavior, health history and ways that can be used to predict the evolution of the person's health. These factors are directly related to the ability of persons to achieve the activity of daily living ADL/IADL [12] [13] such as $eating$, $toileting$, $mealpreparation$ etc. Sensing of such activity, in a smart environment, should be tied to the nature of monitored activity, its repeatability, the duration required to achieve a given activity and the direct impact of the monitoring on the lives of the persons. Therefore, for an efficient monitoring, the sensing frequency should be dynamically updated based on the identified factors and influenced by the detection of abnormal and unusual behavior of the monitored persons. In this work, we aim to come up with an efficient monitoring system based on: the use of optimal sensing frequencies for each activity, a dynamic update scheme of sensing the activities and the prediction of the person's behavior in order to guide the used sensors for an optimal monitoring. We propose a predictive context-aware system with a conditional processing scheme. In this scheme, (Fig. 1), the person's profile which includes the dependency level and historical records represent the essential key to motivate sensor nodes for an optimal sensing frequency in order to process the highly relevant data. Consequently, the proposed approach system deals with the necessity of data collection and the prediction of the person's behavior.

A. *Sensing and evaluation of activities*

In the geriatrics domain, several models are used to describe the person's ability to achieve the activities of daily living (ADL). The evaluation of this ability leads to identify the level of dependency of the person. SMAF [14] [1] is one of the most commonly used models that considers 29 activities classified on five categories. The major considered activities in this work are those defined in the SMAF model (e.g. $eating$, $toileting$, etc.) with an additional set as minor activities (e.g. $watchingTV$, $reading$, etc.). Based on the nature of each activity and the required time to monitor it, the activities are associated with set of dynamic information such as the frequency, duration and score to determine the monitoring mode to be applied. The frequency is used to specify $when$ the monitoring should start while the duration specifies $howlong$ the monitoring should take. To define a monitoring mode, the activities are classified in two categories of monitoring. For instance, in $Category\ I$ which includes activities such as $toileting$, the initial monitoring frequency (i.e. the x value) is 2 and the monitoring duration is 24 hours. For $Category\ II$, including activities like $washing$, the selected frequency (x value) is 3 and the duration is $always\ active$ till the activity occurs. The next round of monitoring is triggered after the x value. Here, the system monitors the $toileting$ activity each 2 days during 24 hours which leads to a total of 15 results during a period P=30 days. Each single result of the 15 results refers to the person success/fail in performing the activity. The variable $activityResults$ represents the number of activities performed correctly. The obtained results are used to progressively judge and compute the person's ability through the duration of the monitoring mode tailored to each activity. The system checks the person's behavior: if the performed activities are lower or higher than the predicted values (mainly in terms of number and duration), the system will detect an abnormal behavior and extends the monitoring for an extra duration period. Otherwise, the system will count the single result, if the observed number after duration of monitoring is greater than or equal to a predefined value. For instance, for the $toileting$ activity, if there is no any detected abnormal behavior and the observed number is greater than or equal to 2, the single result will be considered.

As in any geriatric model, we use scores to evaluate the person's ability to achieve the different activities (i.e. dependency evaluation). We use four scores which are $Autonomous(A)$: 0, $Supervision(S)$: -1, $Needhelp(H)$: -2 and $Dependence(D)$: -3. Since we have four scores, the monitoring result of each activity is evaluated using four intervals with a step of $P/4.x$, where x is the sensing frequency and P is a period of time used to re-evaluate the person's dependency. For example, if we have a positive monitoring result for a given activity which is $activityresults$ = 10, a x value of 2 with a P=30 then, the score intervals are: $D \equiv$ [0, $step$=3.75[; $H \equiv$ [$step$=3.75, 2.$step$=7.5[; $S \equiv$ [2.$step$=7.5, 3.$step$=11.25[and $A \equiv$ [3.$step$=11.25, 4.$step$=15]. Consequently, the activity evaluation here ($activityScore$) has a score of S (i.e. supervision).

B. *Dynamic monitoring mode*

An optimal ecosystem of health monitoring has to determine the degree of data sensing (i.e. frequency) in order to avoid unnecessary data and the exaggerations of the existing dependency models as we presented it in our previous investigation [1]. Therefore, to optimize the monitoring mode, we opt for the person's dependency evaluation as an essential key to increase or decrease the frequency of the monitoring mode. The idea is to provide a dynamic frequency of monitoring by updating the initial x value (discussed previously) according to the person's dependency level and by using one of the existing evaluation models in the geriatrics domain. To reach this objective, and based on our previous investigation [1], we select the SMAF model [14] which defines 14 dependency levels (called also $personprofile$) from $profile$ 1, for autonomous persons, to $profile$ 14 for dependent persons. The system uses the default x value for autonomous persons and then decreases it if there is a decline in the person profile. For instance, if the person belongs to $profile$ 1, the monitoring uses an initial x value set up for each activity (e.g. x=2 for $washing$ activity). When the person's profile increases, the x value dynamically decreases (e.g. $x = x/2$ for $washing$) which implies a more sensing frequency for a higher dependency profiles. This general rule is adopted for all the activities except for the IADL activities. Indeed, for the monitoring of IADL, after decreasing the x value, it should increase again in severe dependency levels where the person becomes near to the called long-term care facilities (LTCF). In LTCF, the person is not able to achieve the IADL activities hence there is no need, for an efficient system, to be in high sensing.

C. Prediction of person's behavior

Despite of the uncertainty caused by the environment and the unstable context of the person's intraday behavior, the data series of the patient's history can help an efficient system to estimate and forecast the future behaviors. Since we aim to sense the high relevant data of the person's context, we opted to model this approach using the Grey Model theory [15] to predict the health condition of elderly person based on the person's behavior and the energy consumption for each activity (e.g. durations and frequencies to achieve $toileting$ activity). Consequently, the system ensures providing a proactive attention with only the relevant data and the ability to notify the caregivers if there is a high probability of decline regarding to the person profile. The Grey Model GM (1, 1) is the widely used in prediction system with incomplete information and is suitable to be applied with short learning periods.

The Grey Model GM (1, 1) is summarized as follows [15]: the system considers a non-negative sequence of initial data: $X^{(0)}$={$x^{(0)}$(1), $x^{(0)}$(2), .. , $x^{(0)}(n)$}. Based on the initial sequence $X^{(0)}$, a new sequence $X^{(1)}$ generated by AGO, the accumulated generating operation, in order to smooth the randomness: $X^{(1)}$={$x^{(1)}$(1), $x^{(1)}$(2), .. , $x^{(1)}(n)$}, where $x^{(1)}(k) = \sum_{i=1}^{k} x^{(0)}(i)$, k = 1, 2, .. , n. The generated mean sequence $Z^{(1)}$ of $X^{(1)}$ is defined as follows: $Z^{(1)}$ = {$z^{(1)}$(2), .. , $z^{(1)}(n)$}, where $z^{(1)}(k)$ = 0.5$x^{(1)}$(k) + 0.5$x^{(1)}$(k-1), k = 2, .. , n.

The first order differential equation of GM (1,1) is defined by: $x^{(0)}(k) + az^{(1)}(k) = b$, so the whitening equation is: $\frac{dx^{(1)}}{dt} + ax^{(1)} = b$. Let

$$Y = \begin{bmatrix} x^{(0)}(2) \\ x^{(0)}(3) \\ \vdots \\ x^{(0)}(n) \end{bmatrix} \text{ and } B = \begin{bmatrix} -z^{(1)}(2) & 1 \\ -z^{(1)}(3) & 1 \\ \vdots & \vdots \\ -z^{(1)}(n) & 1 \end{bmatrix}$$

The a and b parameters can be found as follows:
$[a,b]^T = \left(B^T B\right)^{-1} B^T Y$. According to whitened of GM (1,1), the solution of $X^{(1)}$ at time k is: $x_p^{(1)}(k+1)$= $\left[x^{(0)}(1) - \frac{b}{a}\right]e^{-ak}+\frac{b}{a}$.
Consequently, to obtain the predicted value of the initial data row at time $(k+1)$ we use $x_p^{(0)}(k+1)$= $\left[x^{(0)}(1) - \frac{b}{a}\right]e^{-ak}(1-e^{a})$

D. Scenario Generation

To evaluate our proposed system with the prediction of the person's behavior with an efficient sensing frequency, we need to use rich and realistic scenarios that describe the person's activities for a long period of monitoring. The input scenarios should be close to the real-life and for long-term period. Unfortunately, most of the current studies of the scenarios datasets do not fulfill the real requirements to provide a clear vision regarding the context of person [16]. Therefore, in order to generate a long and rich set of person's activities, we defined a new strategy to generate scenarios by using $Markovian$ models. Mainly, we use the class of variable-length Markov models VMM [17] to obtain a certain expression during the generation process of sequences of daily living activities: $s = a_1, a_2, ..., a_i$ where the a_i is a person action used to perform a given activity. Each a_i has starting time and a random duration D to achieve the activity, where $D \in [aD_{min}$, $aD_{max}]$. There is a random transition time $tT \in [tT_{min}$, $tT_{max}]$ from the end of current a_i to the next starting time of a_j (a_i, a_j). In order to provide a realistic sequences generation, we defined five transition matrices during one day period. Each matrix includes high probabilities for a set of activities that can be achieved within a given period during the day. The main process uses a Markov matrix M_p to generate the next action a_j depending to the probability of M_p (a_i, a_j) where a_i is the current action. Two constraints are used in the generation process: the frequency $f(a_i) \in [f_{min}$, $f_{max}]$ and the total duration of a sequence. The frequency is used to ensure that some a_i should appear at least f_{min} times and do not override f_{max}. The generation process will stop when the total duration of the sequence is exceeded and all the $f(a_i)_{min}$ are satisfied. Our generated scenarios and matrices are detailed online [18].

E. Proposed Algorithm

Based on our proposed methodology, the algorithm simulated data series with time evolution i using different input scenarios generated for one year (act lines). All the considered activities (category I and category II see Section III-A) have a monitoring time ($MTime$) depending on the x value (sensing frequency). The x value varies according to the nature of monitored activity and the monitoring mode. The x value is updated regularly based on the evaluation of person's context (profile). This evaluation is obtained by computing scores associated to the different activities (use Algorithm 1, lines 11, 23 and 39). The activity score is tested with four modalities (A,S,H and D see section III-A) in the $SMAFScore$ function (line 50). Then, the person's profile is computed using the $computeSMAFProfile$ function (line 53). The person's profile determines the new x value and monitoring time for each activity (line 54). Although the incomplete data sequence and for only a short time of monitoring, the algorithm can approximate the person's daily life behavior and predict values based on the duration $Dur(act)$ and repeatability $actno.(act)$ in achieving the different activities. Once the observed behavior satisfies the predicted values, the system will continue the regular monitoring mode (lines 12 and 40), otherwise the system will identify an abnormal behavior (lines 15, 25 and 37) and force the sensors to continue the monitoring (lines 14, 33 and 36) till the behavior becomes as usual. Our Algorithm uses a set of predictive functions regarding different parameters of activities such as durations, repeatability and power consumption. Algorithm 2 gives an example to predict values regarding the duration required in performing the person's activities. The initial data represent the sequence of the person's behavior in terms of average durations used to achieve these activities. If the data raw size is less than 3, the system uses the previously observed average of duration; otherwise the system uses the Grey model to predict next values.

Algorithm 1 Predictive context-aware monitoring

```
procedure PredictiveMonitoring
    A ← activities; N ← year in seconds;
    act ← readLine(inputScenario); MTime(a_i) ← 0;
  ▷ start reading activities & initialize "monitoring time" for all activities
    for i = 1 → N do        ▷ i is the current moment of time evolution
        if i == startingTime(act) then
            switch act do                              ▷ see Section III-A
                case Category I :
                    if i ≥ MTime(act) then
                        compute network traffic and power consumption;
                        if Dur(act) Satisfy PredictDur(act) then
                            activityresults(act)++;
                            updates MTime(act);
                        else
                            ContinueMTime(act);
                            abnormaldetection(act)++;
                        end if
                    end if
                case Category II :
                    if i ≥ MTime(act) and
                      i ≤ MTime(act) + 24h then
                        compute network traffic and power consumption;
                        if Dur(act) Satisfy PredictDur(act) then
                            temporaryactivityresults(act)++;
                        else
                            abnormaldetection(act)++;
                        end if
                    end if
            act ← readLine (inputScenario);
        end if
        for each a in Category II do
            if i ≥ MTime(a) + 24h then
                if abnormaldetection(act) > 0 then
                    ContinueMTime(act);
                else
                    if actno.(act) NSatisfy Predictactno.(act) then
                        ContinueMTime(act);
                        abnormaldetection(act)++;
                    else
                        computeactivityresults (a);
                        updates MTime(a);
                    end if
                end if
            end if
        end for
        if mod (i, 30 days) == 0 then
            compute durbehavior (act) and no.behavior(act);
            Predictpower(act) ← GreyModel(power(act));
            PredictDur(act) ← GreyModel(durbehavior(act));
            Predictactno.(act) ← GreyModel(no.behavior(act));
                          ▷ compute the activityScore (see Section III-A)
            for l = 1 → A do
                activityScore(a_l) ←
                SMAFScore(activityresults(a_l));
            end for
            profile ← computeSMAFProfile(activityScores);
                                ▷ for computing the SMAF score, see [1]
            DynamicMonitoring(profile);
        end if
    end for
end procedure
```

IV. Experimentation

In order to provide efficient sensing frequencies and a prediction of the person's conditions evolution, we have conducted several simulations for the outcome of the person's behavior for a whole year. We used our mentioned algorithm applied on a set of scenarios including a person's profile changes (decline of autonomy) [18]. To evaluate the efficiency of our monitoring system, we compared the proposed system using a continuous

Algorithm 2 Predictive value with Grey Model GM(1,1)

```
function GreyModel(durBehavior(act))
    X^(0) ← {x^(0)(1), x^(0)(2), .. , x^(0)(n)}.
                                        ▷ initial data sequence
    if n < 3 then
        x^(0)(n+1) ← x^(0)(n)
        return PredictDur(act)
    else
        X^(1) ← AGO X^(0).
        [a,b]^T ← (B^T B)^(-1) B^T Y.
                            ▷ compute B and Y see Section III-A
                ▷ Grey tries to find an estimation of "a" and "b"
        x_p^(0) (k+1) ← [x^(0)(1) - b/a] e^(-ak) (1-e^a)
                                    ▷ compute a predicted value
        return PredictDur(act)
    end if
end function
```

monitoring system in terms of: number of monitored activities, energy and network traffic consumption and the detection of abnormal situations. For more flexibility, specifically for network traffic and energy consumption, we consider three classes of sensor nodes: $high$, $medium$ and low used in the monitoring the person's activities. Resources consumption depends on the nature of the sensor used to monitor a given activity. For instance, for the *low* class, we consider typical sensors with standard power values: 10.8mA, 7.5mA and 1μA in the transmitting, idle/receiving and sleeping modes respectively [19]. We simulated a variation of the sensing frequency (i.e. the x value) to ensure and identify the efficient values that combine a good optimization of the resources (computing, network and energy), credibility of dependency evaluation and ensure a high accuracy for the detection of abnormal and unusual situations for all the levels of the person's dependency. We used these values with GM(1, 1) to predict the health conditions of the monitored person based on the behavior and the energy consumption.

Figures 2, 3 and 4 respectively compare the accumulated computing process (number of monitored activities), energy and network traffic consumption between a continuous monitoring and our monitoring system with a set of different x values (frequency of monitoring) using a scenario with profile changes. With X_1, all the considered activities (categories: I and II, see Section III-A) have the same x value which refer to maximum of monitoring which is each day. With X_2, the x value is set to 1 for Category I, and set to 3 for Category II. With X_3, the x value is set to 2 for Category I, and set to 5 for Category II. Finally, X_4 refers to a minimal monitoring hence the x value is set to 3 for Category I, and to 10 for Category II. These changes are as follows: profile P_1 from month 1 to 3, P_3 from month 4 to 6, P_6 from month 7 to 9 and profile P_9 from month 10 to 12. The results presented in figure 2 show that our monitoring system performs a sensing of 61.5% of the activities with X_1, 54.3% with X_2, 35.6% with X_3, and 24.5% with X_4 when compared to a traditional continuous monitoring. Consequently and due to the conditional monitoring that deals only with sensing the required data, the observed gain is of 37.2% for the energy consumption and 38% for the network traffic with X_1, 48.3% for the energy and 49.3% for the network traffic with X_2, 64% for the energy and 64.6% for the network traffic with X_3 and 74% for the energy and 74.3% for the network traffic with X_4

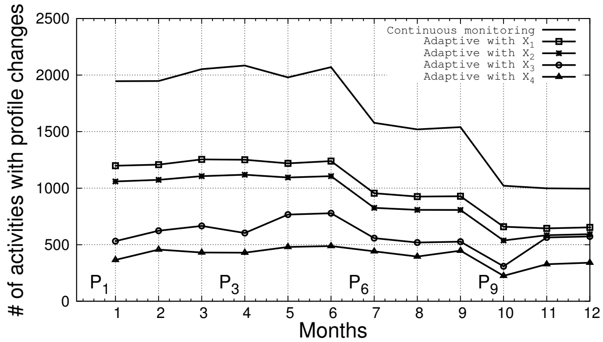

Fig. 2. Number of Monitored Activities with Profile Changes

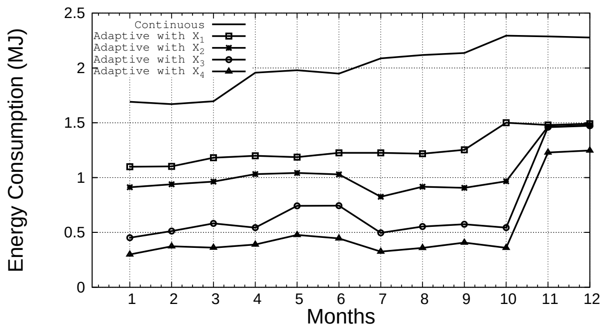

Fig. 3. Energy Consumption

in figures 3 and 4.

Figure 5 compares the accuracy of detecting the abnormal situations using the different sensing frequencies. Recall that an abnormal situation is tied to unusual behaviors in performing the daily activities in terms of duration or repeatability. The X_1 reflects the maximum monitoring frequency and represent a full detection of abnormal situations (462 cases). The abnormal situations appear in the input scenario with particular values regarding the performed activities and their nature such as the duration and frequency of an activity. Any major difference that occurs regarding the achievement of an activity based on prior periods (days or weeks) represent a notable change in the behavior of the person. The results reveal that in spite of the X_2 sensing which is 54.3% of the whole activities, the X_2 frequency matched the performance of X_1 and succeeded to reach 100% of abnormal detection. This result is explained by the fact that the sensing frequency is more context-aware in the sense that it depends on the nature of each activity and the probability to have abnormal situation. For instance, monitoring of $meal\ preparation$ and $washing$ activities is completely continuous and active all time, while monitoring $watchingtv$ and $reading$ is achieved periodically and at low

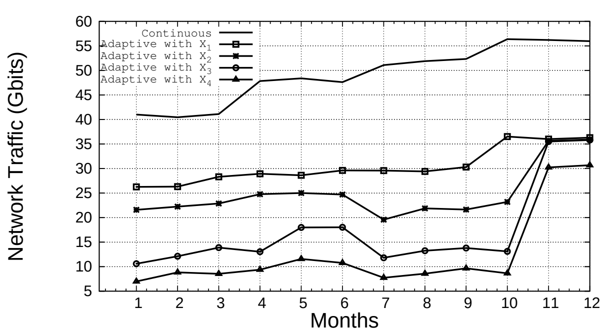

Fig. 4. Network Bandwidth Consumption

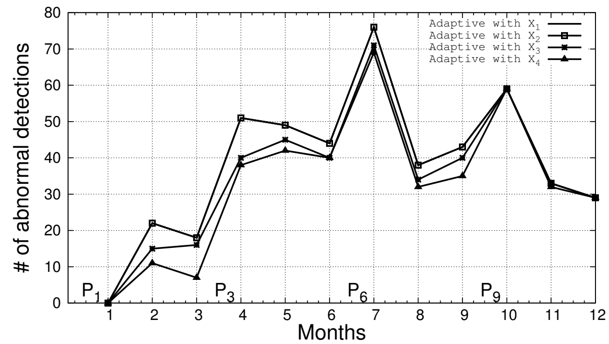

Fig. 5. Classic Detection of Abnormal Situations with Profile Changes

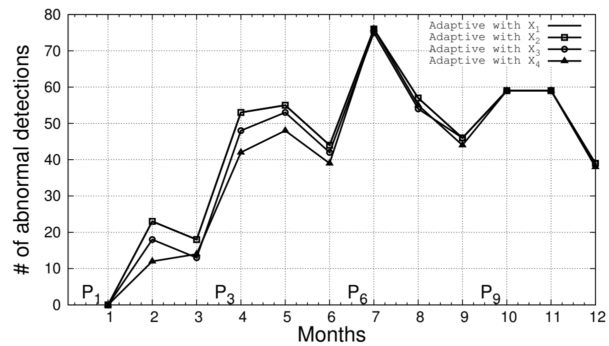

Fig. 6. Detection of Abnormal Situations with Profile Changes Using GM(1,1)

frequency. In the same Figure 5, we can observe a detection of 91.3% with X_3 and 85.3% with X_4.

A robust context-aware monitoring system can be evaluated by how much the vision and knowledge of the person's context is good and how the relevant knowledge is used to timely provide services and assistance. In our context, it requires to ensure a credible dependency evaluation and a high accuracy for detecting of abnormal situations that may represent a risk for the monitored person. The use of the Grey model GM(1,1) helped to predict the evolution of the health conditions based on the behavior and the energy consumption that reflects well the activities of the person. GM(1,1) helped to optimize the monitoring of our system by giving a more accurate map about the person's context which in turn determines the true detection of an abnormal behavior and thus implies a higher data sensing if required. The use of GM (1,1) was evaluated using the sensing frequencies (the x values) presented in figure 2. The first observation on the obtained results is related to the number of abnormal behavior detection, which has increased to 529 instead of 462 in the situation of a continuous monitoring (i.e. with X_1). Thanks to GM (1,1), our system is more intelligent to learn the normal behavior of person and more precise to extract the real deviation in the behavior of the elderly from the norm. The second observation is that our proposed system enriched with the prediction of the person's behavior succeeded to ensure a high accuracy for the detection with the same sensing frequency. Indeed, Figure 6 shows that X_2 succeed with 100% of detection similarly to figure 2, while X_3 succeed to improve the detection with 95.8% and X_4 with 91.9%.

The last results of this work concern the use of the energy consumption as indicator to predict the change of the person's global behavior. In order to achieve this objective, we realized

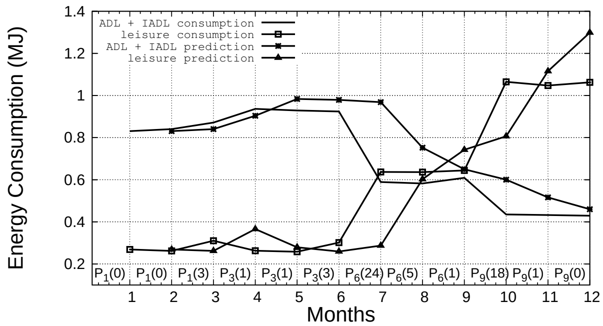

Fig. 7. Prediction of Power Consumption for Detecting a Profile Change

that the person's consumption of energy used in performing the daily tasks can be classified into two main categories. The first includes the energy related to perform ADL and IADL (i.e. the major activities) such as $washing$, $toileting$, $meal\ preparation$, etc. The second category (that we call $Leisure$) includes the energy consumed in monitoring activities such as $watching\ TV$, $reading$ and $sleeping$ (i.e. minor activities). Generally, a person who becomes more dependent tends predominantly to perform less ADL/IADL activities and more activities for leisure with less mobility. Figure 7 shows the real energy consumption used in the monitoring of the ADL/IADL activities and the consumption for the leisure activities for a whole year. The predicted values for these two categories is obtained using the GM(1,1) in our proposed system. Basically, the system detects abnormal situations when the two following conditions are satisfied in the same time. The first condition is satisfied when the power consumption is less than the predicted value for ADL/IADL. The second condition is satisfied when the power consumption is more than predicted value for leisure activities. The results reveal that our system detects 24 changes during the seventh month which reflects a high probability that a significant change has occurred regarding the person's profile. 18 changes were detected during the tenth month. Note that there are zero detection of changes during some months (such as the last month) this is due to the expected energy consumption in leisure activities is higher than the real consumption which makes our second condition unsatisfied.

V. Conclusion

In this work, we proposed a predictive and efficient e-health monitoring for daily living activities in a smart environment. Compared to a full continuous monitoring system, our proposed monitoring approach optimizes the resources, in terms of computing, network and energy, and provides optimal sensing frequencies for high relevant data that are tied to the person's context. For instance with an adaptive and high monitoring (X_2), that ensures a perfect accuracy in detecting abnormal behaviors, the gain was 48.3% for energy consumption, 49.3% for network traffic and a processing of only 54.3% of daily activities. The proposed system automatically evaluates the person's dependency and is able to predict the person's behavior by analyzing a minimum amount of sensed data with a short period of training. The proposed predictive approach has allowed gaining a high accuracy in the detection of abnormal behaviors of monitored persons: 100% of accuracy in high monitoring (X_2), 95.8% in medium monitoring (X_3) and 91.9% with a minimum of monitoring (X_4).

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